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Identifying relationships between key performance indicators

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Abstract

This work has highlighted the importance, from a decision-making point of view, of identifying KPIs relationships. Then, it has presented two main groups of techniques that could be applied: Statistical techniques and multi-criteria decision aid techniques (MCDA). The application of one technique or another will be decided regarding the level of accuracy sought when identifying KPIs relationships as well as the investment to be made. Generally speaking, the application of statistic techniques will be preferred when enough historic KPI data is available though the application of these techniques is usually more resource consuming than the use of MCDA techniques.

Keywords: performance indicators; strategy, relationships.

1. Introduction

Performance measurement systems (PMS) have recognizably become one of the most applied management tools worldwide. A PMS is simple in its conception but it delivers powerful results regarding the control and monitoring of an organisation's performance overtime. In this context, several approaches have been developed such as Cross and Lynch (1988), Kaplan and Norton (1992), etc. All these approaches consisted of defining some key objectives and associated key performance indicators (KPIs). KPIs represent the most operative part of a PMS, providing information about whether associated objectives are being reached or not. Whereas most of the research in this area has looked at the strategic part of the PMS, lower attention has been paid to work on the operative part, as this is mostly seen as a mere operative element of a PMS.

However, in recent years there has been a growing trend affecting both practitioners and academics (Itner and Larker, 2003; Alfaro, 2003) who look at the KPI level as a source of additional meaningful information for organisations. Research on this matter conclude that finding relationships between a set of KPIs, defined within a PMS, will result in a valuable source of decision-making information, providing feedback for the strategic management. Initially, the identification of KPI relationships would allow the reduction of the number of KPIs to be monitored by an organisation. For instance, if it is found that two KPIs maintain a close relationship, as the variation of one provokes the variation of another, it then could be possible to concentrate efforts on controlling and monitoring only one of them. Further, it would allow analysts to check on the indicators' integrity and to construct cause-effect diagrams that would better show the behaviour of KPIs over time. Once relationships between KPIs have been stated, there is another very important way of using this information: To translate these relationships upstream within the PMS. This idea was mentioned by (Alfaro, 2003) who stated that the development of such a system would lead to the dynamically better management of a PMS, as such a system would establish cause-effect relationships between the different objectives derived from strategy. Therefore, an organisation could more closely control and monitor the accomplishment of their stated objectives, as some objectives could have not been reached by the interaction of other objectives. Figure 1 illustrates this idea.

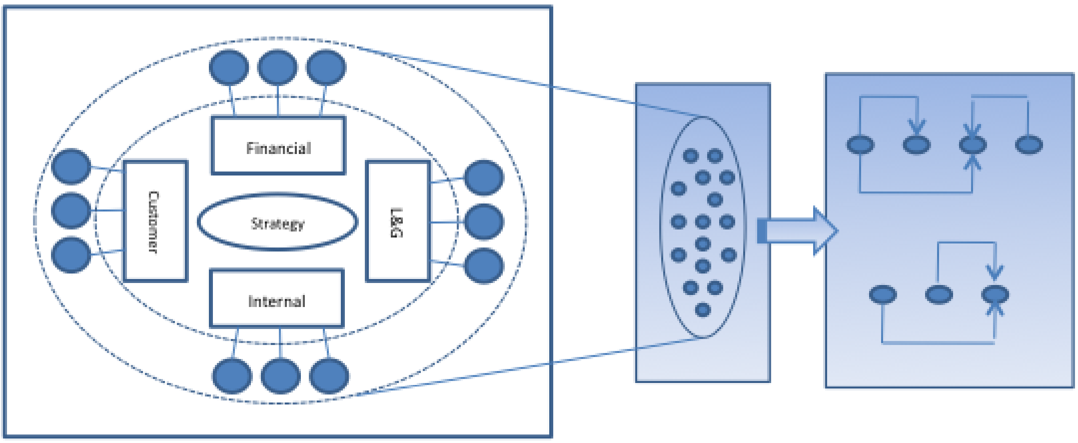

Figure 1. Establishing relationships between KPIs

Data collected by KPIs may come under different units of measure such as monetary units (€,$), time units (minutes, hours, days, etc), percentage (increment/decrement) or different frequencies (yearly, monthly, daily, etc). Initially, this fact will make it more difficult to find relationships between KPIs. Then, the initial data will come in a matrix formed by the different KPIs in the columns, and the observed different values in the rows.

Hence, there is a need to evaluate current efforts for measuring KPI relationships. Accordingly, the main purpose of this paper is to compile the main frameworks or techniques that have been used, and others that could be used for identifying relationships between KPIs defined within a PMS.

2. Identification of KPIs relationships

This section presents the techniques that have or could have been applied at the performance management context for identifying relationships between KPIs at the performance measurement system context. These techniques are the following:

- Statistical techniques.
- Multi-criteria dedicision aid methods.

2.1. Statistical techniques

The nature of the data collected by the different KPIs that an organisation may define made the authors first look at the different statistical techniques that have been applied within the performance management context. Then, it was found that the application of both univariate and multivariate statistical techniques would be, a priori, a suitable solution, as they describe the process of observation and analysis of variables over time (Hair, 1995). From those, the most often used techniques at the performance management context are the following: Correlation, regression analysis, analysis of variance (ANOVA), multivariate analysis of variance (MANOVA).

The *correlation technique* indicates the strength and direction of a linear relationship between two variables (Cohen et al., 2003). A multitude of correlation studies have been conducted at the performance management context. For instance, (Ling, 2004) captured the existing relationships between a firm's internal factors and results of performance indicators by applying a correlation study. Furthermore, the study of trade-offs applied to competitive priorities in organisations is a direct application of correlation studies. Even though some authors (Schonberger, 1986; Skinner, 1992; Hayes and Pisano, 1996) affirm that an organisation does not have competitive, but instead, complementary priorities, others (Skinner, 1992; Slack 1997; Boyer and Lewis, 2002) maintain the existence of such competitive priorities. Authors supporting the latter trend have employed correlation studies between pairs of these competitive priorities such as: Cost versus Quality (Boyer and Lewis, 2002; Schroeder et al, 1996; Filippini et al, 1995; Mapes et al, 1997); Time versus Costs (Perunovic and Christiansen, 2004); Costs versus Suppliers' Relations (Wagner and Jonson, 2003); Customer Satisfaction versus Production Costs (Gupta and Maranas, 2003).

Consequently, the application of correlation analysis is appropriate only when the study aims to find relationships between pairs of variables. Therefore, the current research problem will not initially be solved by applying correlation analysis unless the set of KPIs under study is made out of only two KPIs, which is difficult. Additionally, correlation analysis does not identify interrelationships between a set of KPIs.

On the other hand, *multiple regression analysis* examines the dependence of a dependent variable on other independent variables or predictors (Fox, 1997). For instance, Gomes et al (2004) carried out a multiple regression analysis to study the importance of different information for financial decisions through the usage of 63 KPIs; Van Der Meer et al (2005), through multiple regression analysis, quantifies the relationships between effectiveness measures and level of coordination of rescue services; Koh and Koh (1999) established relationships between the performance of students and six external variables.

However, when applying regression techniques, there is a factor that may come up and needs to be taken into account: Multicollinearity (Fox, 1997). Multicollinearity refers to any linear relationship amongst explanatory variables in a regression model and might lead to the so-called overfitting phenomenon, which consists of the fitting of a statistical model that has too many parameters (Tetko, 1995). A solution to multicollinearity phenomena are the so-called Partial Least Squares Regression Models (PLS) (Wold, 1975). PLS models are adequate to mitigate multicollinearity and advisable when having only a few observations in the data matrix and/or missing values (Nelson et al., 1996; Geladi and Kowalski, 1986; Carot, 2003).

Nevertheless, from its own definition, to create a regression model the analyst must first state what the independent or predictor variables are as well as the dependent variables. This information is not known in advance, as this in one of the main objectives to be achieved in this research. However, it could be possible to estimate the impact of an explaining variable on a dependent one by using the called non-parametric regression techniques such as kernel regression. The main handicap of non-parametric regression is that requires a high number of observations and is computationally intensive (Draper and Smith, 1998).

ANOVA is a technique used for analyzing the relationship between one or several explicative variables (independent variables or factors) and one continuous result variable (Lindman, 1974). ANOVA utilizes an orthogonal decomposition of the sum of squares, thus requiring an orthogonal design for the research. Besides, several conditions must be met: Independence, normality, homocedasticity and linearity (Hair, 1995).

Examples of ANOVA applications in this ambit are: (Garrigos-Simon et al, 2005) applied ANOVA to assess the viability of three different types of competitive strategies and their impact on a firm's performance; (Edwards et al, 2003), through the application of ANOVA, checked whether some sport KPIs made a distinction among different types of participants that have different physical capabilities; (Szymanski et al, 1995) used ANOVA to find out whether the entrance order of different types of products was associated with market share.

On the other hand, *MANOVA* is a generalization of ANOVA when there are several result variables, and following the explanation given about ANOVA, it could be discarded as a solution to identify and quantify relationships between KPIs defined within a PMS context. Examples of MANOVA in the context of the present research are: Manacci et al (1999) applied MANOVA for determining whether six performance factors were affected by works conditions; Houghton et al (2001) determined, with MANOVA analysis, whether the quality of primary care in a hospital was influenced by different types of management; Huizingh (2002) applied MANOVA to establish whether different customization styles influenced the performance indicators definition of a website.

Hence, although difficult to apply in this context, ANOVA and MANOVA should not be discarded yet as possible solutions at this point. What it is clear is that prior to their application the analyst must verify the above commented conditions.

The main advantage of using statistical techniques to identify KPIs relationships is that the results achieved are not based neither on experience nor on subjective judgments of the decision-maker, as they analyse data sets directly. However, data handling –storage, collection and transfer- and analysis will be surely a much more resource consuming process.

2.2. Multi-criteria decision aid methods

The multi-criteria decision aid methods (MCDA) establish a ranking of the different competitive priorities for maximizing performance according to some given criteria (Da Silveira, 2005). The main MCDA methods are the following:

- Objective programming.
- Hierarchical techniques.

Objective programming uses lineal models to provide the best solution to a problem with multiple competitive priorities. The Data Envelopment Analysis (DEA) is one of the most commonly applied techniques within the performance management ambit (Chen et al., 2006).

Hierarchical techniques are characterized by the establishment of a hierarchy made up of different levels, each of them including several decision alternatives (Da Silveira, 2005). The main hierarchical techniques are AHP and ANP. AHP (Saaty, 1980) is a tool for making decisions that has been widely used in the performance management ambit. AHP carries out pair-wise comparisons, through correlation analysis, between competitive priorities, subjectively establishing a numeric scale for measuring performance from both a qualitative and a quantitative point of view. On the other hand, ANP (Saaty, 1996) is a technique that complements AHP by also considering the interrelationships between the factors affecting performance.

The main advantage of applying MCDA techniques for identifying KPIs relationships is that it is not necessary to deal with a large historic data set, as they rely rather on experience. However, the resulting KPIs relationships might not be as exact as by applying statistical techniques.

3. Classification of techniques

This section classifies the techniques previously pointed out. To do so, different factors have been taken into account:

- Type of decisions: Objectivity/Subjectivity.
- Type of relationships: Pair-wise relationships/multi-relationships.

According to these factors, it is possible to classify the different techniques above presented as it can be seen in Figure 2. Then, from a decisional point of view, the techniques have been classified into either objective (when they manipulate real data) or subjective (when they are based, in any of their steps, in applying personal experience/judgement). On the other hand, from a relationships point of view, the techniques have been classified into either pair-wise comparisons techniques (when they are able to only capture relationships between two variables) or multi-comparison techniques (when they are able to identify relationships in a data set at once).

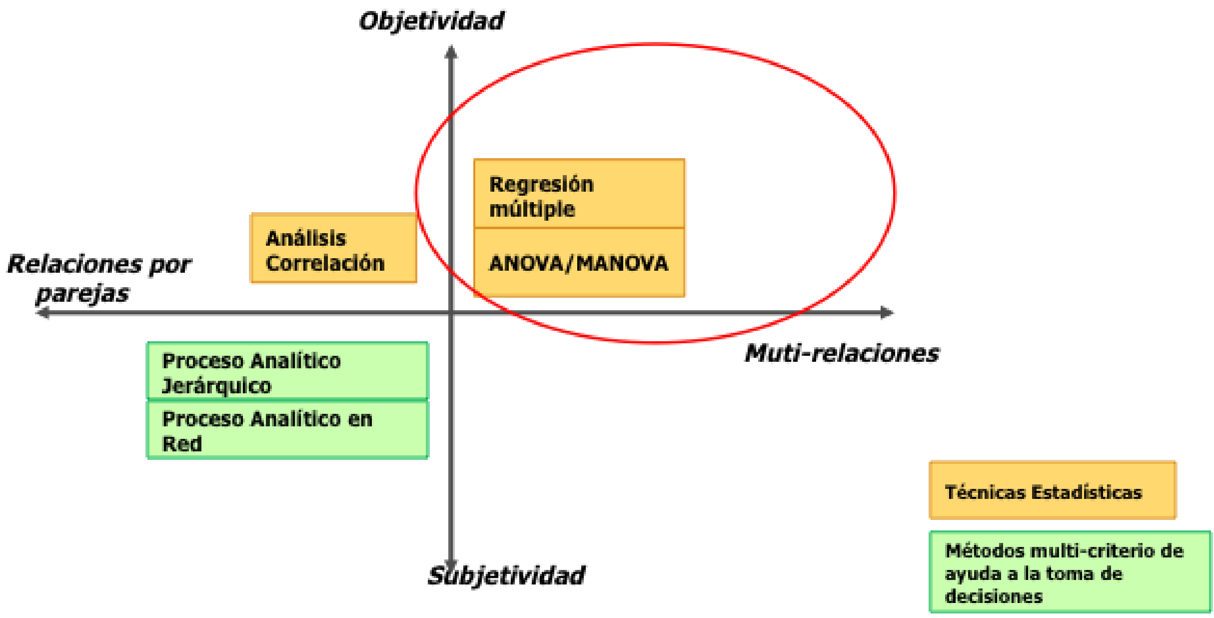

Figure 2. Classification of techniques

Then, it is possible to affirm that the statistical techniques are objective (as they manipulate real data) and that the MCDA techniques are subjective in nature. On the other hand, only some statistical techniques (ANOVA/MANOVA, multiple regression) are able to identify relationships in a data set at once instead of only capturing relationships between a pair of performance indicators.

If there are enough data available from the performance indicators it is recommended to apply statistical techniques, though this can be more resource consuming than if using the MCDA.

From a real life enterprise point of view, it will be always possible to apply MCDA techniques as they are based on gathering personnel's opinions and judgements regarding a specific issue. In this particular case, the person/people in charge of identifying relationships among performance indicators will ask to the enterprise's experts whether there are relationships or not among some performance indicators. Some sort of architecture such as a survey supports usually this process. The surveyed personnel will tick in a Lickert scale whether they think that there is a relationship or not; to do so, they can rank the relationship (if any) from a value of 1 (weak relationship) to a value of 9 (strong relationship). When they have rank all the relationships they think that exist, the results obtained are computed and finally transformed into a mathematical quantified relationship.

Looking at the statistical techniques, it is possible to affirm that their application to this problematic would objectively set out the relationships among performance indicators. However, there is a noticeable problem when using statistical techniques in this performance management context: there may not be enough data to obtain meaningful results. This is due to the fact that a performance measurement system is dynamic in nature and it is continuously being revised and changed. Then, it is easy to think of the strategic objectives that were set for a specific period of time (usually one year) to be replaced by new ones. Such a strategic objectives replacement, as a consequence of the rethinking/strategic enterprise repositioning, will also bring new performance indicators. Then, for a period of time it is logical to find lots of performance indicators and some of them with only one annual observation. Then, for an initial performance indicators data matrix, it is not unusual to find matrices with lots of columns (performance indicators) and relatively few observations. There will be lots of gaps within the matrices and this will enormously difficult the analysis process.

Hence, analysts have to decide whether they apply either the subjective MCDA techniques or the objectives statistical ones. The decision will have to be made following mainly two main criteria: The available resources and the historic performance measures data available to carry out the analysis.

4. Conclusions

This work has highlighted the importance, from a decision-making point of view, of identifying KPIs relationships. Then, it has presented two main groups of techniques that could be applied: Statistical techniques and multi-criteria decision aid techniques (MCDA). The application of one technique or another will be decided regarding the level of accuracy sought when identifying KPIs relationships as well as the investment to be made. Generally speaking, the application of statistic techniques will be preferred when enough historic KPI data is available though the application of these techniques is usually more resource consuming than the use of MCDA techniques.

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